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A review on the applications of driving data and traffic information for vehicles' energy conservation

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A B S T R A C T

A large portion of energy consumption in the world is related to transportation. In recent decades, a variety of technologies have been innovated and applied in order to decrease vehicles energy consumption. In this paper, a comprehensive review on the use of driving data and traffic information for vehicles energy conservation is done. The main aim of this paper is the development of a framework for classification and comparative assessment of various methods and technologies, in which driving data or traffic information are utilized for vehicles energy conservation. The applications are classified into three main categories including (1) traffic monitoring and management systems, (2) intelligent energy management systems in vehicles and (3) intelligent management of charging issues. Research topics in each category are explained and their respective effectiveness in vehicles energy consumption reduction is discussed. The review concludes that the use of the driving data and traffic information leads to remarkable improvements in vehicles energy consumption reduction.

Contents

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1. Introduction

Energy conservation is a much discussed topic all over the world due to the depleting energy resources as well as the impact to the environment. Energy sources are mainly categorized into two groups which are nonrenewable and renewable. Nonrenewable energy sources such as fossil fuels energies can deplete over the years. On the other hand, renewable energy sources can be reproduced in a short time such as wind, water and solar energies. Energy sources are mainly consumed in industry, transportation, agricultural, commerce and civil areas [95-98].

The energy consumption in the transportation sector is known to be very large, of which the vehicles are responsible for most of the energy consumed [1]. In the worlds terminal energy consumption structure, the total energy consumption is at 6212 million tons of oil equivalent (mtoe), in which the transportation sector consumed 1831 mtoe, equivalent to 29.5% of the total energy consumed [2].

In an effort to reduce the consumption of energy by vehicles, various technologies have been innovated and applied, especially in the consumption of fossil fuels as well as electrical energy. Examples of such technologies are lean-burn engines [3], continuously variable transmission [4] and alternative-fuel vehicles such as electric, hybrid electric and plug-in hybrid electric vehicles which are the most successful achievements in this area. Many previous studies have proven the effectiveness of such modern vehicles comparing to conventional vehicles in energy conservation.

More recently, studies on the effect of using driving data and traffic information for energy conservation are actively done. Traffic information and driving data analysis have many applications in various areas such as intelligent transportation systems (ITS), traffic flow modeling [5–7], pollutant emissions dispersion investigation [8–10], accident prevention and safety [11,12], etc.

This review paper encompasses historical and ongoing research into the applications of driving data and traffic information in energy consumption reduction in vehicles. These applications are classified into three categories in this study, including (1) traffic monitoring and management systems, (2) intelligent energy management systems in vehicles and (3) intelligent management of charging issues. Each category is also divided into some research topics as demonstrated in Fig. 1.

2. Driving data and traffic information: definitions and characteristics

As this paper deals with the applications of driving data and traffic condition information in vehicles energy conservation, it is necessary to introduce some definitions in this area. In this section, a short description of expressions, definitions and characteristics of driving data is made, followed by the description of the driving data, driving segments, driving features and traffic conditions.

2.1. Driving data

Driving data includes date/time, longitude, latitude, speed and altitude of vehicle in every second. Driving data gathering can be performed using Advanced Vehicle Locating (AVL) devices. The AVL device (shown in Fig. 2) works using Global Positioning System (GPS) and is placed inside the car. The velocity of the vehicle is considered as a very important driving data because the driving segments and driving features are defined based on velocity time series.

2.2. Driving segments

A driving segment is defined as the velocity values in a period of time with a distinct length. Four consecutive real driving segments with length of 150 s are illustrated in Fig. 3. The driving time series partitioning is performed for data characteristics analysis. Another common method for driving data time series partitioning is micro-trip which is defined as velocity profile from stop to stop. Fig. 4 depicts six real consecutive micro-trips on the same velocity profile.

2.3. Driving features

Driving features are defined and used for analysis of driving segments characteristics. Various driving features have been defined in the previous studies [13–15]. For example two of these driving features are average velocity (V_{ave}) and variance of velocity

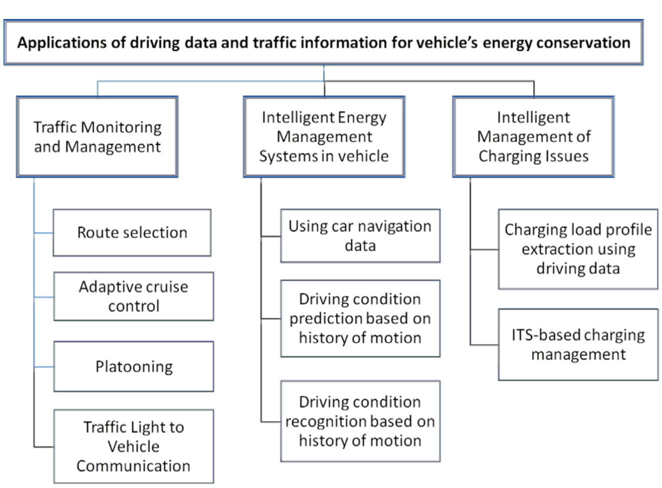

Fig. 1. Applications of driving data and traffic information for vehicle's energy conservation.

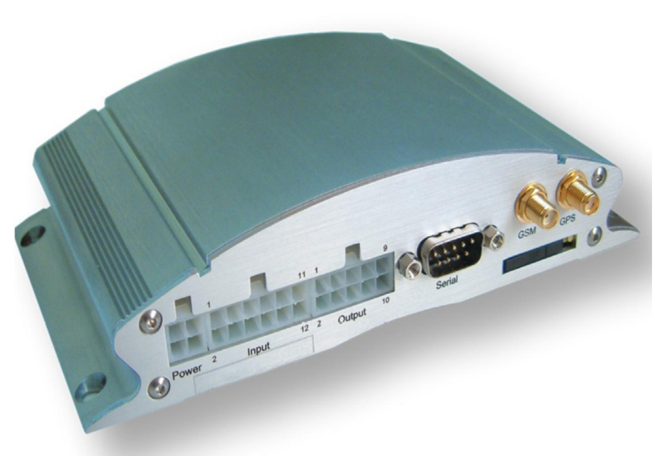

Fig. 2. An AVL device.

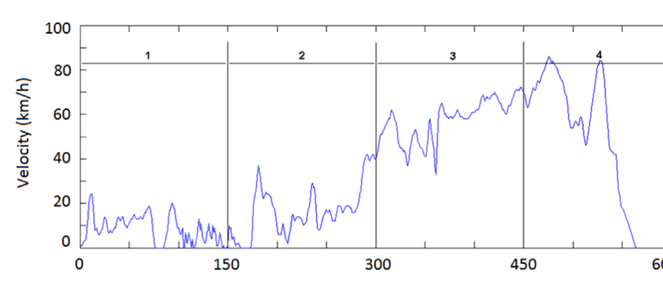

Fig. 3. Four consecutive real driving segments.

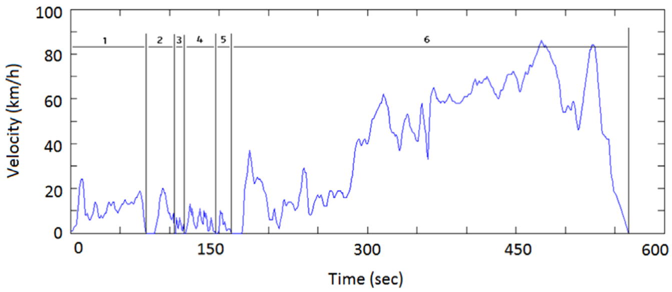

Fig. 4. Six consecutive real micro-trips.

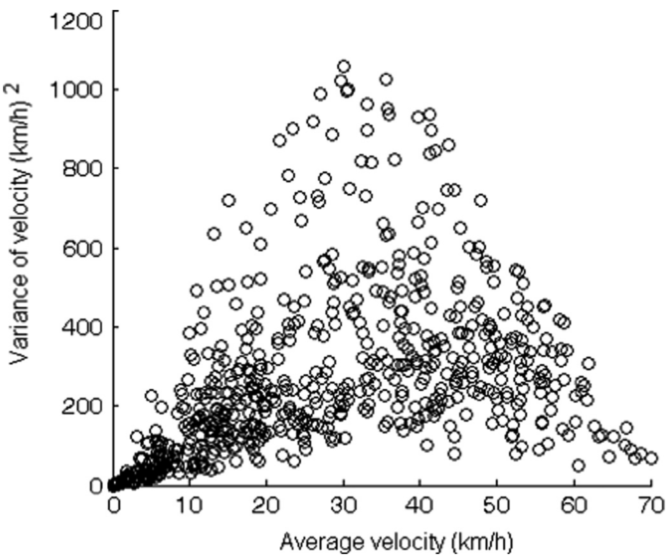

Fig. 5. Scatter plot of a group of real driving segments in feature space.

(σ_v) which are formulated as follows, where parameter n is the driving segment length and v_i is the velocity in the ith second:

$$V_{ave} = \frac{1}{n}\sum_{i=1}^{n} v_i \tag{1}$$

$$\sigma_v = \frac{1}{n}\sum_{i=1}^{n} (v_i - V_{ave})^2 \tag{2}$$

In Fig. 5, the distribution of a real cluster of driving segments is depicted in driving feature space. In this scatter plot, each point corresponds to one driving segment. The figure contains a range of 0–70 km/h for average velocity and 0–1200 $(km/h)^2$ for variance of velocity, demonstrating difference between driving segments.

In Fig. 6, two real sample driving time series are illustrated. They have been obtained using the AVL devices in one of our previous works. After partitioning these two velocity time series into 150-s segments and extracting their driving features, two plots are obtained as demonstrated in Fig. 7. In this figure, segments of samples A and B are highlighted with black color among all driving segments. Such scatter plots can be utilized for driving data analysis and traffic condition recognition.

Traffic conditions are defined based on driving features. For example using only one driving feature such as average velocity, driving segments can be classified into three groups as follows: (1) congested traffic condition including driving segments with average velocity between 0 km/h and V_1 km/h, (2) urban traffic condition including driving segments with average velocity from V_1 km/h to V_2 km/h, (3) highway traffic condition including driving segments with average velocity more than V_3 km/h. Using another driving feature like variance of velocity, driving segments can be

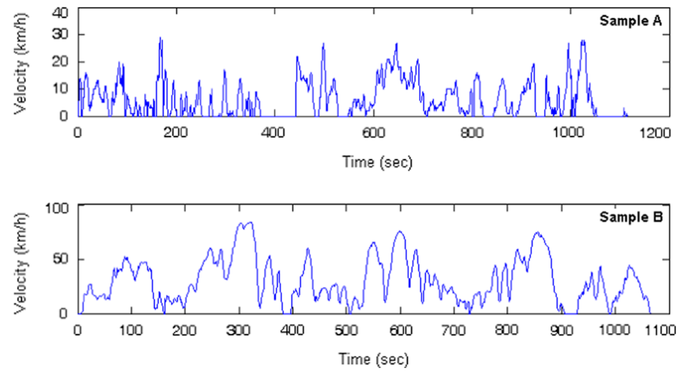

Fig. 6. Two sample driving time series (samples A and B).

clustered in 2-dimensional driving feature space. Different numbers and combinations of driving features have been investigated for traffic condition definition and recognition in [16].

3. Vehicles energy consumption reduction using traffic monitoring and management systems

Due to the need to conserve energy globally, efforts are made to use the driving data and traffic information in the application for vehicles energy consumption. One area of application is the traffic monitoring and management systems. Traffic information can be supplied by vehicle telematics [17] or Intelligent Transportation Systems (ITS) which can provide vehicle autonomous functions using GPS navigation technology [18].

Two types of communications exist in ITS including road-to-vehicle and vehicle-to-vehicle. In road-to-vehicle communication, vehicles send and receive data to and from the stations beside the road. A schematic of vehicle-to-vehicle information delivery is illustrated in Fig. 8. In such system each car communicates with the other cars in its neighbor [19].

In the following, some technologies and methods based on traffic monitoring and management systems that lead to vehicles energy conservation are described briefly.

3.1. *Proper route selection as a driver support tool*

Today, many driving assist tools have been designed to increase driving safety, increase comfort by providing useful information for driver and reduce the environmental effects of driving. Among these tools, the navigation support tool has been developed to decrease energy consumption and emission of vehicles via a navigation system. In this approach, there is a route choice optimization problem which is based on the lowest total energy consumption [20]. A navigation system which has been used in Lexus Gen V vehicle is shown in Fig. 9.

One mechanism for the implementation of rout choice tools is the vehicular ad hoc network (VANET). VANET is a type of mobile ad hoc networks (MANET) that work based on short-range communications technologies. VANETs have been gaining much attention over the past years. Their significance has been known in industry, academic and governmental organizations [21–23]. The main advantage of ad hoc network ITS is that it does not need any infrastructure. So the cars can communicate anywhere and drivers become aware of traffic conditions in their path [24]. Consequently, vehicles energy conservation is possible via the proper route selection.

It is demonstrated in [20] that for 46% of trips the drivers do not choose the most fuel-efficient routes in Lund city. It is shown

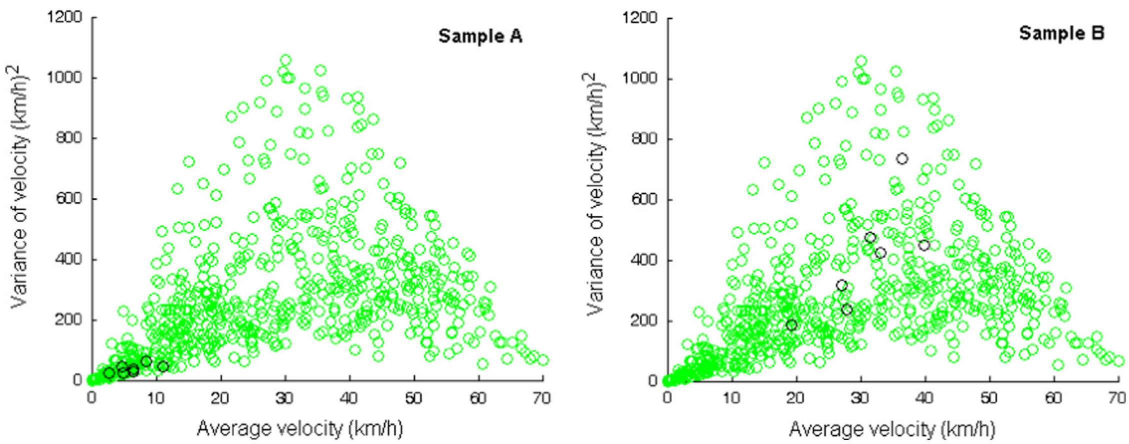

Fig. 7. Segments of samples A and B, highlighted among all driving segments.

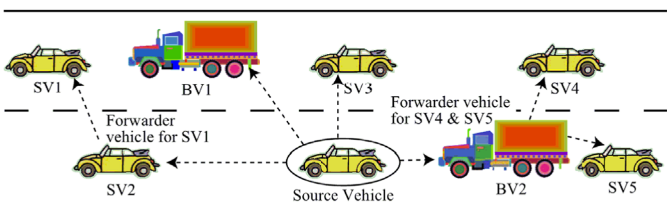

Fig. 8. Vehicle information delivery in ITS [19].

Fig. 9. Lexus Gen V navigation system.

that by using a fuel-optimized navigation system, 8.2% improvement in vehicles' fuel consumption is achieved in these trips.

3.2. Adaptive cruise control systems

One technology in which the intelligent traffic management systems can improve energy conservation in vehicles is Adaptive Cruise Control (ACC) system. ACC systems improve and speed up the traffic flow while keeping safety on the highways. Their function is based on maintaining a constant time-gap between cars during motion [25]. Using this system, vehicles can move faster and more freely and consequently less energy is wasted. Fig. 10 shows a schematic of the ACC system in vehicles.

A special ACC for electric vehicles (EVs), called Slipstream Cooperative Adaptive Cruise Control (SCACC) technology, reduces energy consumption and extends the EV range using ITS. This system is applied while driving behind and near another vehicle (shown in Fig. 11). The concept is based on air drag force reduction for the following vehicle. Consequently, more energy conservation can be achieved and EVs are able to go longer distances [26]. In Table 1, some quantitative results of implementation of SCACC technology based on experimental tests on a typical vehicle are summarized [27]. As demonstrated in the table, the less distance exists between the vehicles, the more energy is saved. But it should be noted that decreasing the distance between vehicles makes the need for safer and more reliable braking systems that should be regarded in separate studies.

3.3. Platoon system as an energy-saving ITS technology

Platoon system has been originated from a national project called "energy ITS" in Japan in 2008. The aim of the project was vehicles' pollutant emission and energy consumption reduction. In this system, some vehicles (especially freight cars) move in tandem as a unit. A schematic of a platoon system is illustrated in Fig. 12 [28]. The mechanisms of this system for energy conservation are to prevent unnecessary accelerations and decelerations during motion, avoiding traffic jams using ITS and reducing aerodynamic drag force by minimizing the distance between vehicles. it should be noted that safety and reliability are two vital aspects in utilizing this technology [28].

3.4. Traffic light to vehicle communication technology

As idling and sharp accelerations/decelerations increase vehicle's pollutant emissions and energy consumption [29], they should be prevented as much as possible. Utilizing modern communication technologies, it is practical for vehicles to receive light signals and other data in road junctions. Based on this traffic signal data, in [30] an arterial velocity planning method has been designed that gives useful advices to drivers in order to adjust their velocity to face green lights in intersections. In this algorithm, idling, accelerations and decelerations are minimized while ensuring that the vehicle never exceeds the speed limit. Using this technology, energy conservation of about 12–14% has been obtained by velocity planning [30].

The above-mentioned technology is used in traffic-light-to-vehicle communication (TLVC) systems. Based on the simulation results in the study for a single vehicle and traffic light, TLVC

Fig. 10. Schematic of the ACC system.

Fig. 11. SCACC system [26].

Table 1
Vehicle energy consumption reduction using SCACC at 89 km/h [27].

Distance between vehicles (m)	Energy consumption reduction (%)
30	11
15	20
6	27
3	39

system can decrease fuel consumption by up to 22% [31]. Recently, TLVC has received an increasing amount of attention due to its benefits to individual drivers even at low penetration rates of the new communication technology. In [32], application of the TLVC technology is investigated especially for electric vehicles. Their assessments have revealed that electric vehicles can also benefit from TLVC up to 20% improvement in energy conservation by changing the way of accelerating and decelerating.

4. Intelligent energy management systems in vehicles using driving data and traffic information

As mentioned before, hybrid vehicles are vehicles equipped with at least two different sources of energy. In order to use the two power sources of HEV effectively, a control unit is necessary for suitable management of energy distribution. The control unit calculates the share of each power source in supplying the required power and the amount of energy that should be saved. HEV control unit manages the energy aiming at minimizing vehicles energy consumption and exhaust emissions and also providing satisfactory performance [33–35]. A comprehensive overview of different types of HEV and PHEV control strategies can be found in [36,37] respectively.

Complex nature of the control strategy and its interconnection with hybrid powertrain design make HEV energy management problem critical. In addition to the complex nature of the problem, if the control strategy is not well-suited to vehicle configuration, even a good design could lead to non-optimal hybrid operation. So optimization of HEV control strategies is an important topic in this area. HEV control strategy optimization has been investigated in many previous studies [38–40].

Because of the influence of the traffic conditions on the optimization of HEV power management system, applying an adaptive control approach is essential. This approach suggests that a HEV requires high ability to adapt itself to current traffic condition to minimize fuel consumption and exhaust emissions. The use of driving data and traffic information in an adaptive or intelligent HEV power management system has become an interesting subject for research [41–44].

In the following, techniques and methods in which driving data and/or traffic information is used in a vehicle energy management system for energy conservation are explained.

4.1. *Intelligent HEV energy management using car navigation data*

One source for utilizing traffic information in vehicles energy management system is car navigation data provided via global positioning system (GPS), vehicle geographical information system (GIS) or vehicle telematics. In this section, methods and approaches in which the navigation data is used to improve vehicles energy consumption are introduced.

In [45] an intelligent HEV controller based on driving condition prediction using car navigation data has been proposed. In order to test the proposed method a commuting route to work has been considered. The prediction is done in the path based on a database and on-line location information [45,46]. Consequently HEV energy management system can make better decisions about power distribution between internal combustion engine and electric motor based on battery state of charge (SOC) and future driving condition. This leads to less energy consumption and emissions in vehicle. Fig. 13 demonstrates a block diagram of this approach.

A predictive on/off controller has been designed for a micro-turbine powered HEV in [47]. The proposed controller works based on the prediction of remaining driving distance, average energy demand and a defined time correction factor, which are estimated using a database and GPS navigation system. Performance of the predictive on/off controller has been investigated by simulating vehicle on different driving cycles. The results demonstrate that using the predictive controller leads to 32% to 48% improvement in fuel consumption reduction over NEDC driving cycle comparing to the traditional on/off controller [47].

Application of the route preview in vehicle's energy conservation has also been studied in [48] for a HEV. For this purpose, in-vehicle 3-D maps and vehicle GPS-based navigation system are utilized. In order to decouple the influence of velocity variation,

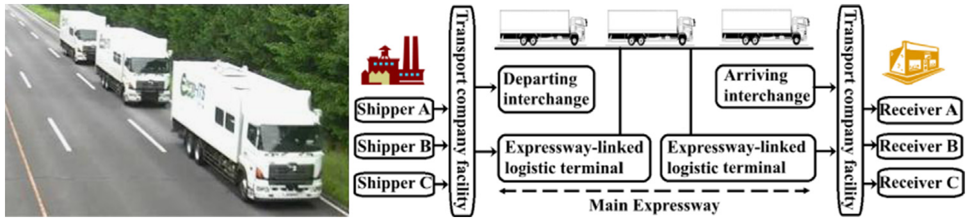

Fig. 12. Schematic of platoon system [28].

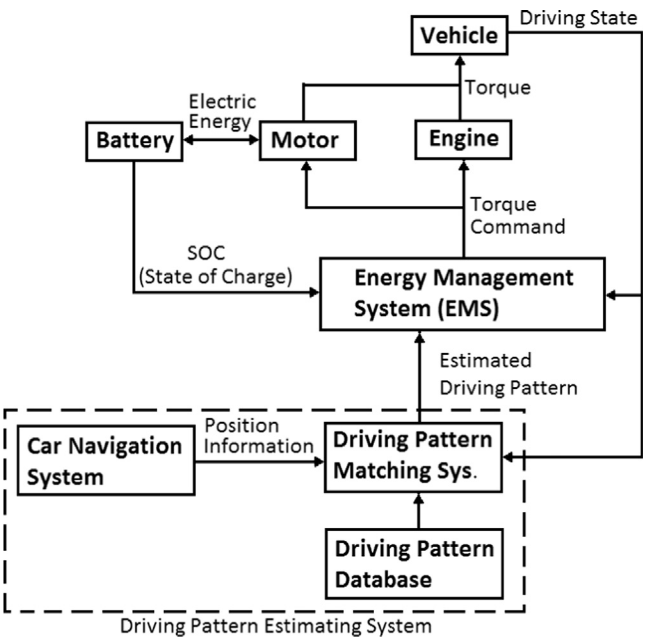

Fig. 13. Intelligent HEV energy management using car navigation data [46].

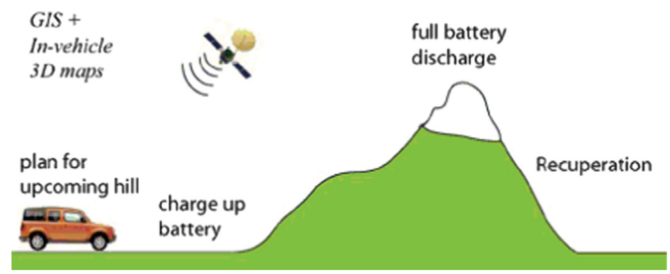

Fig. 14. Intelligent energy management using terrain map [48].

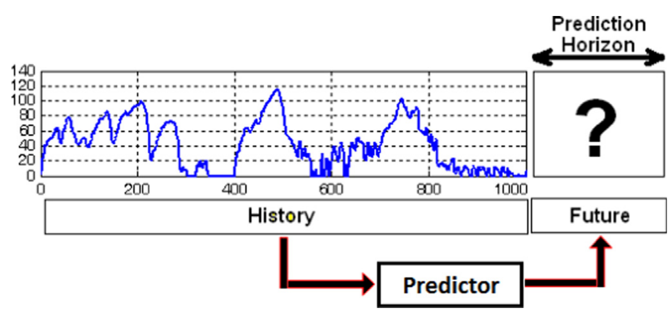

Fig. 15. Schematic of a driving pattern prediction system.

the study has been done in constant-velocity condition. Having route preview and velocity value, intelligent management of energy in HEV is performed. Fig. 14 shows schematic of the predictive energy management based on 3-D terrain maps. Some of the main conclusions of this study are: (1) an average fuel economy improvement of 1%–4% is possible with terrain preview, (2) the improvement is inversely correlated to the cruising speed; i.e., it decreases at higher speeds, (3) preview also reduces the average energy flow to and from the battery and, therefore, may increase the battery's life [48].

Following [48], a simulation case study in [49] has demonstrated that the route preview can also be applied for a PHEV in order to proper selection of pure electric or mixed usage of ICE and electric motor regarding to distance to the next charging station.

In [50] the terrain information has been utilized in an in-wheel motor electric ground vehicle for maximizing the travel distance. In addition, in this study both varied and constant velocities along the terrain profile have been investigated and comparison of energy consumption at different constant velocities has been done. It is demonstrated that 12.5% improvement in battery energy conservation is obtained using the optimal velocity for the given terrain profile.

Road grade and temperature preview are used in EV power energy management and heating systems in [51]. In this approach, the energy management system has been optimized for minimizing battery electric energy consumption, maximizing the temperature comfort in the driver compartment and minimizing the travel time.

Beside an intelligent HEV energy management system, an automatic gear shifting system can also benefit from terrain information. In [52] a predictive gear shift control strategy for a parallel HEV has been designed. Simulation results of the predictive gear shift control strategy on NEDC and FTP-75 driving cycles demonstrate 7.5% and 22.5% improvement in energy consumption respectively.

4.2. Driving condition prediction based on history of motion for intelligent HEV control

In another HEV control method based on prediction of future driving patterns, a predictor is used instead of car navigation system. The difference between this method and the technique presented in Section 4.1 can be explained as follows. In the previous technique, traffic information is supplied via the ITS system but here the method is basically different and prediction is performed regarding to the history of motion. In this method, the driving data is gathered and analyzed inside the vehicle and no on-line information is needed from outside. In other words, this method is also applicable in places in which no ITS infrastructure exists.

Fig. 15 depicts a schematic representation of driving time series prediction system that predicts velocity time series in prediction horizon based on history of vehicles motion. In the figure, the predictor may be a hidden Markov model, a regression-based model or a neural network (NN). Because most of the predictors in the literature are NNs, here we focus on NN. NNs are powerful tools for prediction and they have been applied in different areas such as market forecasting and climate prediction. Especially in the area of driving data and traffic flow prediction, NN has been

used in many previous studies for vehicles movement prediction and vehicle load forecasting [53–55].

In [56] a Multi-Layer Perceptron (MLP) NN [57] has been trained to predict velocity values to 10 s ahead (NN output) based on past velocity time series (NN input). The actual and predicted velocity values in a sample test for 10 s ahead are illustrated in Fig. 16. Results of the Auto Regressive (AR) method [58] are also presented beside the NN results. Both methods should be compared to actual data which has happened in real driving data gathering.

Fig. 17 illustrates a schematic of an adaptive HEV control strategy based on driving time series prediction. In this approach, the prediction horizon is 10 s and the act of prediction is repeated each 10 s. The last driving time series data is used as inputs of NN in on-line situation. Then velocity time series is predicted by NN in near future. The control unit benefits from an off-line database containing many driving segments and corresponding optimized controllers for the segments. After prediction in each step, the most similar driving segment in the database to the predicted segment is selected, and its corresponding controller parameters are used for 10 s. This process is repeated each 10 s during motion. More details about the method and prediction results can be found in [56]. Different lengths of prediction horizon or prediction window sizes are investigated in [59]. It is demonstrated that applying such a predictive controller in vehicle power management system leads to 1.5%–2.7% improvement in vehicles energy conservation over real driving cycles [59].

4.3. Driving condition recognition based on history of motion for intelligent HEV control

Another type of intelligent HEV control strategy, that utilizes driving data in order to reduce energy consumption, is sub-optimal control strategy using driving condition recognition (DCR). In this method, at first the HEV controlling actions are optimized for different driving cycles or driving segments in off-line condition. Then the optimization results are stored in controllers database. In on-line application, DCR sub-system recognizes current driving condition using history of vehicles motion. After that, regarding to the current driving condition, the most similar condition in the database is selected and corresponding optimized controller is used. The recognition process is repeated in regular time intervals in on-line application. Fig. 18 depicts a schematic representation of an intelligent HEV controller using DCR. By this way, the HEV control system can adapt itself intelligently regarding to driving data history. Consequently an improvement is achieved in vehicles energy consumption.

Because the optimized controller is not exactly optimized for the current driving condition, it is called sub-optimal, nearly optimal or semi-optimal. It should be noted that the optimized controller suffers from limitations in on-line application such as the time needed for the optimization and lack of knowledge about the next driving profile in the near future. In the optimization problem, a cost function, which is the sum of vehicles energy consumption (EC) and exhaust emissions (EE), is minimized over a

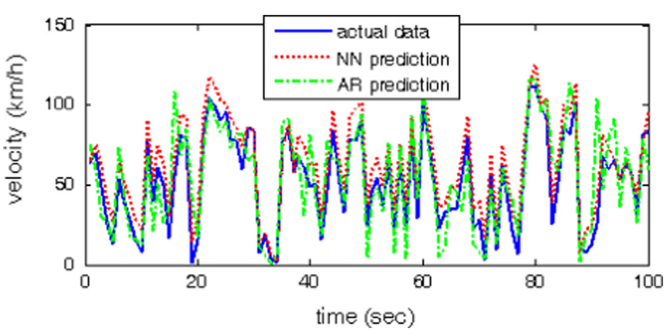

Fig. 16. Actual and predicted values of velocity in 10 s ahead using AR and NN [56].

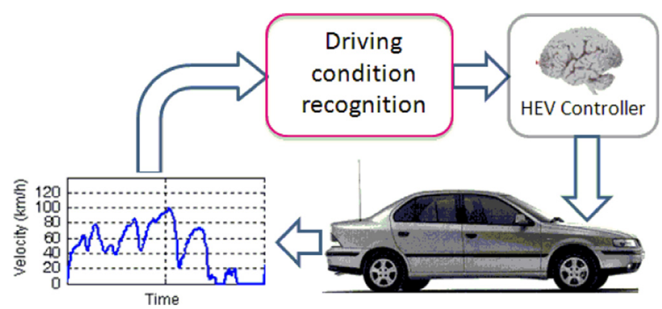

Fig. 18. Intelligent HEV control loop based on driving condition recognition.

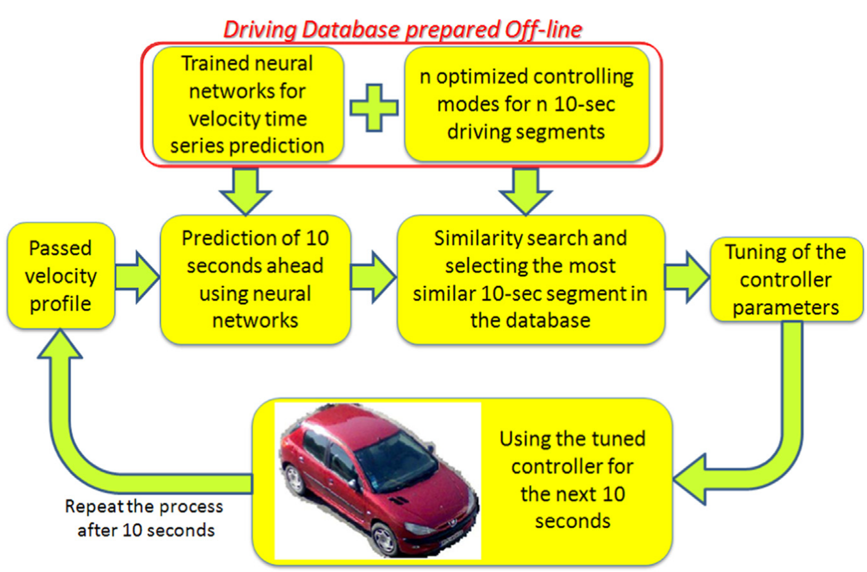

Fig. 17. Schematic of an adaptive HEV control based on driving time series prediction [56].

driving cycle such as follows:

$$cost(x) = \frac{1}{w_1 + w_2}\left(w_1 \int_0^{T_{DC}} (EC)\, dt + w_2 \int_0^{T_{DC}} (EE)\, dt\right) \quad (3)$$

where x is a vector in solution space (X), w_i is a weight that is considered for each factor reflecting its importance and T_{DC} is the time of driving cycle.

It should be noted that in Fig. 18, type of the HEV controller is not determined. Indeed, DCR can be added to different types of HEV control strategies. In the following some control strategies which a DCR sub-system is added to them are presented from the literature.

In [60,61], a multi-mode control strategy has been developed for a HEV. The designed controller has six modes corresponding to six representative driving cycles. The rule-base HEV controller has been optimized using dynamic programming (DP) method for each of the six cycles and optimal control laws have been saved. After that, an on-line DCR sub-system has been designed to switch between the six modes.

In another case study the above-mentioned method is applied in Taiwan [44]. Nine driving patterns in Taiwan are considered in the database. HEV controller has been optimized in off-line condition for all 9 patterns using DP method. The results demonstrate an improvement of 2.06% to 3.18% for the multi-mode approach comparing to the original single-mode approach.

In another similar study [62] an optimized on-line control strategy for a PEM fuel cell-battery hybrid electric scooter has been developed including two phases: (1) off-line optimization and (2) on-line controller design. Phase 1 develops the proper power split ratio between fuel cells and battery set. DP method is applied for the optimization. Phase 2 chooses NN to construct the non-linear relationship between road conditions and optimal outputs according to the first phase. In other words, NN works as a DCR unite here, with a two-layer NN trained via four indices and polynomial coefficients which are derived from the DP (off-line) results. Applying the DP+NN method, the nearly optimized on-line control strategy aimed to reduce the hydrogen consumption (extend the cruising mileage) can be achieved [62].

The study presented in [63] also contains an off-line optimization and NN design for real-time application. The particle swarm optimization (PSO) method has been applied for optimizing control strategy in a PHEV on a driving cycle. Then because of the limitations of optimization in real-time, NNs are trained to utilize the PSO results in on-line condition. So a near-optimal real-time controller is obtained using NN. Comparisons between PSO off-line controller and NN real-time controller have been made for same drive cycles in [63].

In another study in this area, a mixed control strategy (MCS) based on discriminating the current driving condition has been developed [64]. The MCS is a combination of two control strategies including motor assistant control strategy (MACS) and real-time optimization control strategy (RTOCS). The MACS acts well in congested traffic and RTOCS acts well in freeways [38,64]. In MCS, the power management is done based on MACS concept in congested and flowing driving conditions and it is done based on RTOCS concept in country road and highway driving conditions. DCR sub-system detects current driving condition in real-time applications. So the MCS can act better than both if it can benefit from a DCR unit.

In Fig. 18, if a fuzzy logic controller is used as HEV controller, an intelligent fuzzy energy management system is obtained which can adapt itself to current driving condition. In this approach, fuzzy logic HEV controller is designed and optimized in various driving conditions. Here the optimization process consists of finding the most effective shapes of membership functions in order to minimize a cost function such as that presented in Eq. (3). The shapes of membership functions can be parameterized as depicted in Fig. 19. So the solution vector (x) containing x_1–x_5

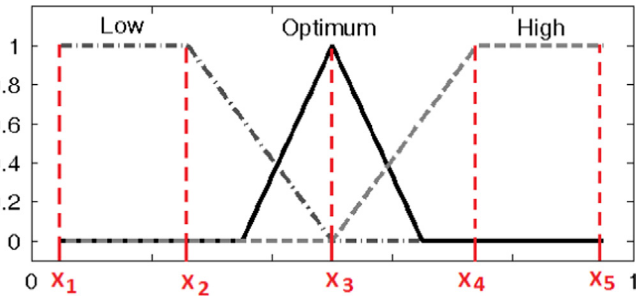

Fig. 19. Fuzzy logic controllers membership functions parameters.

should be determined based on the off-line optimization results for each driving condition. In real-time applications, shapes of membership functions of the fuzzy logic controller are changed regarding to the DCR data. More details about this approach can be found in [65–68].

Another control method called equivalent consumption minimization strategy (ECMS) [69,70] can be used in Fig. 18 as HEV controller instead of fuzzy logic controller. DCR sub-system can also be applied for the ECMS that leads to adaptive equivalent consumption minimization strategy (A-ECMS) [71–73]. The ECMS provide a near-optimal HEV control solution for a driving cycle. In this method, an equivalent factor is used to obtain equivalent fuel consumption for electrical energy usage. So effectiveness of this approach depends on the equivalent factor value. Because the optimal value of the factor changes in different driving conditions, ECMS is not applicable in real-time [74]. In the A-ECMS method, the equivalence factors are changed based on DCR. So it is applicable for on-line power management. In this approach the equivalence factors are adjusted regarding to current driving condition to optimize energy consumption in real time.

5. Intelligent management of charging issues for EVs and PHEVs using driving data and traffic information

The last category of driving data and traffic information applications in vehicles energy conservation is focused on charging and discharging of EVs and PHEVs in order to decrease energy consumption. The topic of charging/discharging EVs and PHEVs has become one of the most significant issues in the recent years. Because of the dynamic characteristics of power grid and variations in electric power demand during a day, many studies are focused on smart grid management intelligently. The driving and traffic information, as well as the electricity real-time price information in the market can play a vital role in this area.

In [75,76], three different electricity demand response options including real time pricing (RTP), time of use (TOU) and flat are investigated for PHEV charging regarding the distribution network in a smart grid environment. In [77], optimal EV charging time profile is obtained respect to electricity price during a day. In this method, communication facilities and real time electricity price information are used to design an optimal load management strategy for a smart grid. Readers interested in a broader discussion in this area are referred to [78–80].

In this study, previous researches are reviewed in which the driving data and traffic information are utilized in order to manage the EVs and PHEVs power demands more efficiently. The literature review is presented in two separate parts as follows.

5.1. Charging load profile extraction using driving data

One approach, in which driving data is used for intelligent management of EVs and PHEVs charging demands, is optimal

charge scheduling based on charging load profile (CLP) extraction. CLPs are affected by the number and types of vehicles, their all-electric range (AER), driving patterns, vehicles daily mileage, charging start time and charging level [81]. For example, Fig. 20 shows number of vehicles needing charge vs. time of day based on the National Household Travel Survey (NHTS) database [82]. The figure demonstrates various charging demands during a day which is utilized for CLP development. In [83], a method for building CLPs for PHEVs based on NHTS data has been described.

As depicted in Fig. 20, there are charging demand peak times during a day which should be managed through applying some policies. In one policy, vehicles arriving during off peak times should be charged at high levels, and those arriving during peak hour times should be charged at low levels. In another policy, the peak points are shifted by not to charge vehicles right at their arrival time. In this policy, vehicles arriving at peak time would have to wait for 2 h to start charging [81].

In [84], a mathematical model of EV charging demand has been proposed which predicts the time and number of vehicles that will arrive to the charge station. The model requires driving data including vehicles number and speeds in the neighborhood. Using these models, proper size of energy storage systems can be determined regarding to CLP. In addition, renewable energy sources can be used by flexible charging strategies to reduce charging cost as illustrated in Fig. 21. This will be practical by using an intelligent load management system (ILMS) to link EVs and PHEVs to renewable energy sources. ILMS requires information about the departure time and length of drivers upcoming trips to manage the charging process depending on the availability of renewable energy in the grid [85].

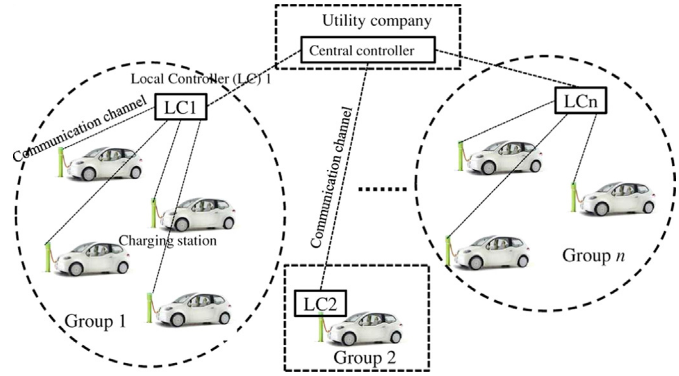

Fig. 22. Locally optimal charge scheduling scheme [89].

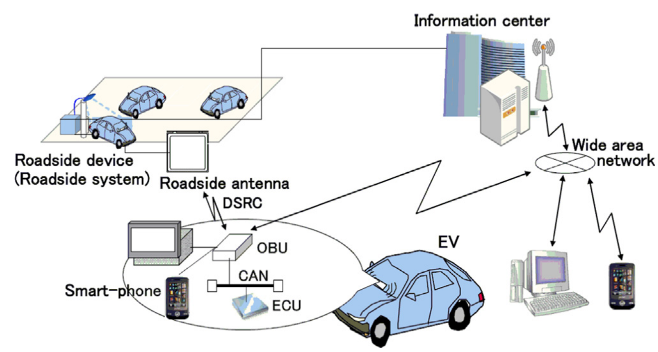

Fig. 23. A schematic of ITS information communication system for EV [92].

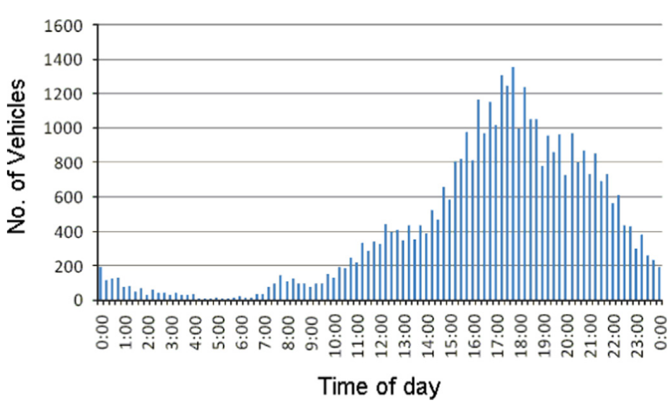

Fig. 20. Number of vehicles arriving each hour [81].

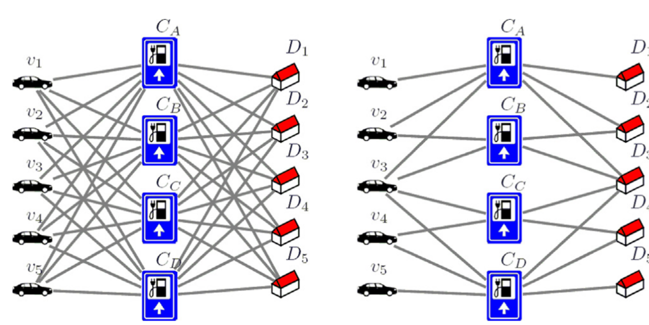

Fig. 24. The full-access (left) and the butterfly (right) scenarios [93].

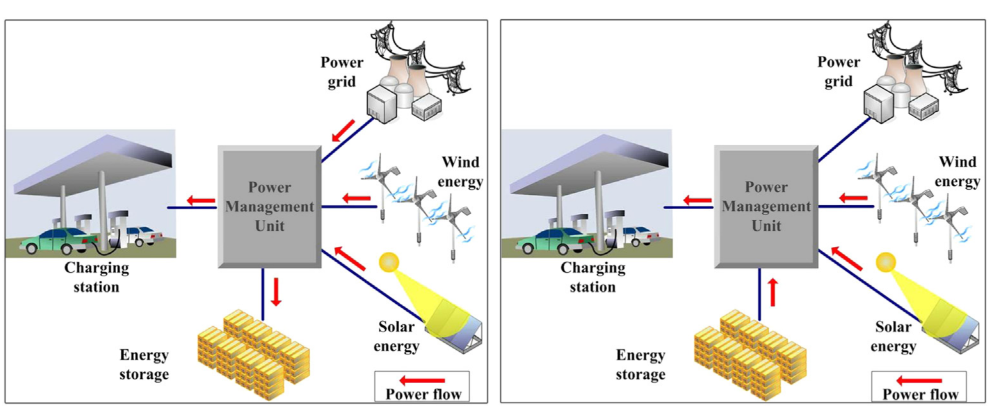

Fig. 21. Flexible charging strategies during peak time (right) and off-peak time (left) [84].

After the extraction of CLPs for EVs and PHEVs, their charge patterns can be optimized in order to get different objectives such as less energy cost and more battery longevity [86–88]. EVs and PHEVs charging and discharging scheduling have been stated as an optimization problem in [89]. In that work, a locally optimal charge scheduling scheme has been developed based on vehicles groups in separate regions. In each region, a local controller (LC) exists and they communicate as shown in Fig. 22.

In addition, grid impact assessment can be performed based on EVs and PHEVs CLPs. In [90], peak power increase in the grid as a function of penetration of PHEVs and EVs has been investigated. It is demonstrated that using CLPs, a coordination strategy can be designed for damping the effects of load change in grid due to EVs and PHEVs charging. The results demonstrate 23% improvement in grid voltage deviation and 4.7% improvement in grid power losses by coordinated charging in condition of 30% penetration rate of EVs and PHEVs [90].

5.2. ITS-based charging management of EVs and PHEVs

Applying conventional charging scenarios without using ITS leads to peak demands. ITS technologies can be utilized in EV and PHEV charging process via a smart charging plan to decrease these peak demands. Using ITS, the electrical grid load can be monitored on-line and electrical energy price can rise in peak times [91].

In [92], an ITS information communication system for EV has been proposed that uses a wide area network, a road to vehicle communication, and an in-vehicle network as a system. Fig. 23

Table 2
Applications of driving data and traffic information in vehicles energy conservation.

Method/technology	Section no.	Notes	References
Proper route selection as a driver support tool	3.1	Guiding driver to select proper routes with the least traffic or length	[20–24]
Adaptive cruise control system	3.2	Preventing unnecessary acceleration and deceleration especially in highways	[25,26]
Platoon system	3.3	An energy-saving ITS technology in which cars move tandem as a unit to prevent unnecessary accelerations/decelerations, avoiding traffic jams using ITS and reducing aerodynamic drag force	[28]
Traffic light to vehicle communication technology	3.4	In this technology, idling, accelerations and decelerations are minimized while ensuring that the vehicle never exceeds the speed limit	[30–32]
Intelligent HEV energy management using car navigation data	4.1	Driving condition prediction using GPS and making a terrain preview to make proper energy management decisions	[45–52]
Driving condition prediction based on history of motion for intelligent HEV control	4.2	Driving condition prediction using in-vehicle instruments to make proper energy management decisions	[53–56]
Driving condition recognition based on history of motion for driving condition	4.3	Driving condition recognition using in-vehicle instruments to adapt energy management system regarding to current	[60–74]
Charging load profile extraction using driving data	5.1	Smart charging scheduling and management usingCLPs	[75–84]
ITS-Based charging management of EVs and PHEVs	5.2	Charging scenarios in which drivers are assisted through ITS for selection of a proper charge station to reduce peak demands	[85–87]

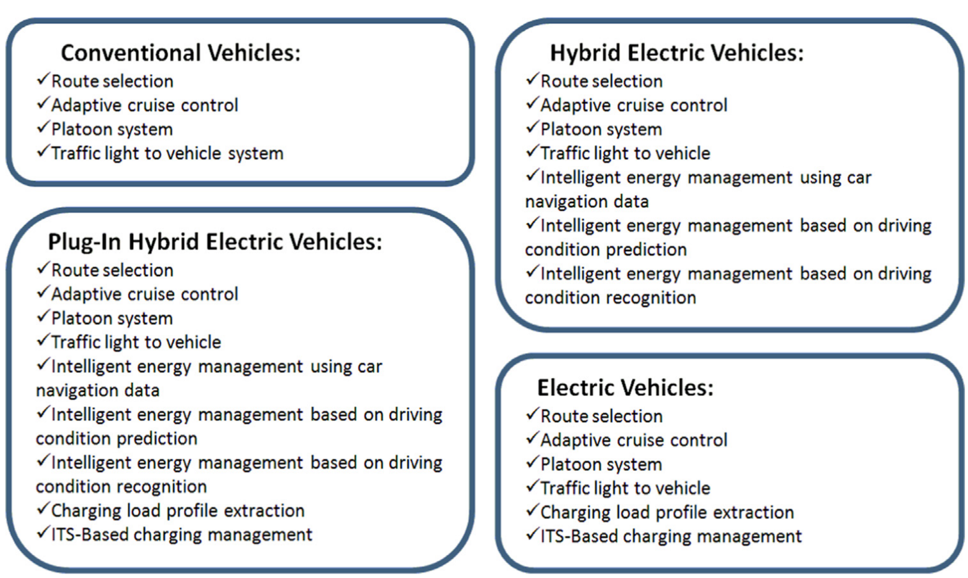

Fig. 25. Classification of energy conservation approaches for different types of vehicles.

shows a schematic of the system. Using this system, EV battery state of charge is observed and managed via ITS communication and EV is conducted to a proper charge station in its proximity.

In [93], charging scenarios have been presented in which EV drivers are assisted through ITS for selection of a charge station. In this approach, different situations are investigated using a game-theoretic method to determine the least-crowded or the fastest trip. The results demonstrated benefits of ITS comparing to the case where drivers have knowledge of the road topology and the charging stations location only. Using ITS, various charging scenarios are applicable. For example, Fig. 24 illustrates two different charging scenarios including full-access scenario in which all vehicles can access any of the existing charging stations, and butterfly scenario in which not all EV flows can reach all charging stations, as shown.

6. Summary and conclusions

In this study, various applications of driving data and traffic information in vehicles energy conservation have been classified and discussed. Table 2 summarizes all mentioned techniques and methods in this paper. In addition, classification of energy conservation approaches is demonstrated in Fig. 25 for different types of vehicles.

This research shows that driving data and traffic information have significant benefits for vehicles energy conservation. All cited studies have demonstrated that applying those techniques and methods leads to an improvement in vehicles energy efficiency and a decrease of the transportation energy sector.

Because of increasing concerns about the environment and higher fuel costs, EVs are considered to be more important than the past. Many car manufacturers have paid more attention to EV technology in recent decade and a renewed interest is observed in this area. One of the most significant issues for utilizing EVs and PHEVs is their charging through the grid. Ongoing researches for EVs and PHEVs are addressing their move toward wireless charging. An experiment of wireless power transfer at Hori Lab is shown in Fig. 26 [94]. Applying this new technology for vehicles charging will prepare the ground for using driving data and traffic information more effectively in vehicles energy conservation in the future.

Fig. 26. Experiment of wireless power transfer at Hori Lab [94].

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References

[1] Mahlia T, Saidur R, Memon L, Zulkifli N, Masjuki H. Renew Sustain Energy Rev 2010;14:3092–9.
[2] Jia S, Peng H, Liu S, Zhang X. J Transp Syst Eng Inf Technol 2009;9:6–16.
[3] Katoh K, Iguchi S, Okano H. In: Wiener motorensymposium; Tokyo. p. 38–44.
[4] Nakajima Y. Jpn J Resour Environ Meas 1995;31:32–44.
[5] Nagel K WR, Wagner P. Jpn J Resour Environ Meas 1995;31:32–44.
[6] Kerner BS. The physics of traffic: empirical freeway pattern features, engineering applications, and theory. Berlin, Germany: Springer; 2004.
[7] Kerner B, Klenov S, Hiller A. Nonlinear Dyn 2007;49:525–53.
[8] Dirks KN, Johns MD, Hay JE, Sturman AP. Atmos Environ 2003;37:2719–24.
[9] Chan T, Ning Z. Atmos Environ 2005;39:6843–56.
[10] Fotouhi A, MontazeriGh M. Int J Environ Res 2012;6:61–70.
[11] Lee J, Li J, Liu L, Chen C. In: Proceedings of the Pacific-Rim symposium on image and video technology (PSIVT), vol. 4319. Hsinchu, Taiwan: Springer, 2006, p. 504–12.
[12] Langford J, Koppel S. Older drivers' safety and mobility: current and future issues. Transp Res Part F: Traff Psychol Behav 2006;9:309–21.
[13] Ericsson E. Transp Res Part D: Transp Environ 2000;5:337–54.
[14] Ericsson E. Transp Res Part D: Transp Environ 2001;6:325–45.
[15] MontazeriGh M, Fotouhi A, Naderpour A. J Mech Eng Sci Part C 2011;225:1301–17.
[16] MontazeriGh M, Fotouhi A. Scie Iran 2011;18:930–7.
[17] Nora S, Minc A. The computerization of society: a report to the president of france. Massachusetts, USA: MIT Press; 1980.
[18] Gerland H. In: Proceedings of the IEEE-IEE vehicle navigation and information systems conference; 1993. p. 606–11.
[19] Naito K, Sato K, Mori K, Kobayashi H. In: Eighth international conference on networks (ICN '09). p. 427–33.
[20] Ericsson E, Larsson H, Brundell-Freij K. Transp Res Part C: Emerg Technol 2006;14:369–83.
[21] Taleb T, Sakhaee E, Jamalipour A, Hashimoto K, Kato N, Nemoto Y. IEEE Trans Veh Technol 2007;56:3337–47.
[22] Taleb T, Ooi K, Hashimoto K. In: Wireless communications and networking conference (WCNC 2008). IEEE; 2008. p. 2212–17.
[23] Zoghi H, Tolouei M, Siamardi K, Araghi P. In: 11th international IEEE conference on intelligent transportation systems (ITSC 2008); 2008. p. 408–13.
[24] Vaqar S, Basir O. IEEE Wirel Commun 2009;16:40–6.
[25] Wang J, Rajamani R. In: Proceedings of the 2002 American control conference, vol. 5; 2002. p. 3690–95.
[26] Kloiber B, Strang T, de Ponte-Muller F. In: 2012 IEEE international electric vehicle conference (IEVC); 2012. p. 1–5.
[27] Busters M. Drafting for money (2007 season); 2011. Available at: 〈http://www.test.org/doe/〉.
[28] Suzuki Y, Ishizaka H, Sakuma A, Kawashima H, Aoki K, Aki M, et al. In: 2011 14th international IEEE conference on intelligent transportation systems (ITSC). p. 1138–43.
[29] Barth M, Mandava S, Boriboonsomsin K, Xia H. In: 2011 IEEE forum on integrated and sustainable transportation system (FISTS). p. 182–8.
[30] Mandava S, Boriboonsomsin K, Barth M. In: 12th International IEEE conference on intelligent transportation systems (ITSC '09); 2009. p. 1–6.
[31] Tielert T, Killat M, Hartenstein H, Luz R, Hausberger S, Benz T. In: Internet of things (IOT); 2010. p. 1–8.
[32] Tielert T, Rieger D, Hartenstein H, Luz R, Hausberger S. In: 2012 12th international conference on ITS telecommunications (ITST); 2012. p. 232–7.
[33] Bumby J, Forster I. IEE Proc on Control Theory Appl D 1987;134:373–87.
[34] Jeon S, Jo S, Jo H, Park Y, Lee J. In: Spring conference proceeding of Korea society of automotive engineers, vol. 2. Kwang-ju, Korea, 1999, p. 713–9.
[35] Won J-S, Langari R. Expert Syst 2002;19:4–10.

[36] Çağatay Bayindir K, Gözüküçük MA, Teke A. Energy Convers Manag 2011;52:1305–13.
[37] Wirasingha S, Emadi A. IEEE Trans Veh Technol 2011;60:111–22.
[38] Johnson VH, Wipke KB, Rausen DJ. SAE Trans 2000;109:1677–90.
[39] Kheir NA, Salman MA, Schouten NJ. Math Comput Simul 2004;66:155–72 (selected papers from the 4th {IMACS} symposium on mathematical modelling).
[40] Sundstrom O SP, Guzzella L. In: Proceedings of the world congress of the international federation of automatic control, vol. 17. South Korea. p. 4642–47.
[41] Lin C, Jeon S, Peng H, Lee J. Veh Dyn Syst 2004;42:41–58.
[42] Musardo C, Rizzoni G, Staccia B. In: 44th European control conference on decision and control (CDC-ECC '05); 2005. p. 1816–23.
[43] Langari R, Won J-S. In: 12th IEEE international conference on fuzzy systems, vol. 1 (FUZZ '03); 2003. p. 290–5.
[44] Chen B-C, Wu Y-Y, Hsieh F-C. In: IEEE international conference on systems, man and cybernetics, vol. 2 (SMC '06); 2006. p. 1022–9.
[45] Ichikawa S, Yokoi Y, Doki S, Okuma S, Naitou T, Shiimado T, et al. In: IEEE intelligent vehicles symposium; 2004. p. 161–6.
[46] Yokoi Y, Ichikawa S, Doki S, Okuma S, Naitou T, Shiimado T, et al. In: 30th annual conference of IEEE industrial electronics society, vol. 2 (IECON 2004); 2004. p. 1727–32.
[47] Geng B, Mills J, Sun D. In: IEEE international conference on robotics and biomimetics (ROBIO); 2011. p. 1468–73.
[48] Zhang C, Vahidi A, Pisu P, Li X, Tennant K. IEEE Trans Veh Technol 2010;59:1139–47.
[49] Zhang C, Vahidi A. IEEE Trans Control Syst Technol 2012;20:546–53.
[50] Li X, Chen Y, Wang J. In: American control conference (ACC). Montréal, Canada; 2012. p. 4993–8.
[51] Grossard M, Kachroudi S, Abroug N. In: IEEE international symposium on industrial electronics (ISIE); 2012. p. 1708–13.
[52] Ngo V, Hofman T, Steinbuch M, Serrarens A. In: Vehicle power and propulsion conference (VPPC). IEEE; 2011. p. 1–6.
[53] van Lint J, Hoogendoorn S, van Zuylen H. Transp Res Part C: Emerg Technol 2005;13:347–69.
[54] Vlahogianni EI, Karlaftis MG, Golias JC. Transp Res Part C: Emerg Technol 2005;13:211–34.
[55] Zheng W SQ, Lee DH. J Transp Eng 2006;132:114–21.
[56] Fotouhi A, Montazeri M, Jannatipour M. Int J Automob Eng 2011;1.
[57] Haykin S. Neural networks: a comprehensive foundation. 2nd ed.. New York, NY: Prentice Hall; 1999.
[58] Robert A. Introduction to time series analysis and forecasting with applications of SAS and SPSS. Massachusetts, USA: Academic Press Inc.; 1999.
[59] Murphey Y, Chen Z, Kiliaris L, Park J, Kuang M, Masrur A, et al. In: IEEE international joint conference on neural networks (IEEE world congress on computational intelligence) (IJCNN 2008); 2008. p. 3755–61.
[60] Lin C, Peng H, Jeon S, Lee J. In: Proceedings of the advanced vehicle control conference. Hiroshima, Japan. p. 234–9.
[61] Jeon S, Jo S, Park Y, Lee J. J Dyn Syst Meas and Control 2002;124:141–9.
[62] Hung Y, Tsai J, Hsu C. In: Proceedings of the international symposium on advanced vehicle control, Taipei, Taiwan. p. 135–40.
[63] Lin X, Banvait H, Anwar S, Chen Y. In: American control conference (ACC); 2010. p. 5037–42.
[64] Huang X, Tan Y, He X. IEEE Trans Intell Transp Syst 2011;12:453–65.
[65] Langari R, Won J-S. IEEE Trans Veh Technol 2005;54:925–34.
[66] Won J-S, Langari R. IEEE Trans Veh Technol 2005;54:935–53.
[67] Ryu J, Park Y, Sunwoo M. J Power Sources 2010;195:5735–48.
[68] Ganji B, Kouzani A, Khayyam H. In: 2011 IEEE international conference on fuzzy systems (FUZZ); 2011. p. 2335–41.
[69] Serrao L, Onori S, Rizzoni G. In: Proceeding of the American control conference. St. Louis, MO. p. 3964–69.
[70] Paganelli G, Guerra T, Delprat S, Santin J, Delhom M, Combes E. Inst Mech Eng, Part D: J Automob Eng 2000;214:705–17.
[71] Musardo C, Rizzoni G, Staccia B. In: 44th IEEE conference on decision and control and 2005 European control conference (CDC-ECC '05); 2005. p. 1816–23.
[72] Gu B, Rizzoni G. In: Proceedings of ASME international mechanical engineering congress and exposition, vol. Parts A and B; Massachusetts, USA. p. 249–53.
[73] He Y, Chowdhury M, Pisu P, Ma Y. Transp Res Part C: Emerg Technol 2012;22:29–41.
[74] Onori S, Serrao L, Rizzoni G. In: Proceedings of ASME dynamic system and control conference. Massachusetts, USA. p. 449–505.
[75] Raghavan S, Khaligh A. In: 2012 IEEE PES innovative smart grid technologies (ISGT); 2012. p. 1–7.
[76] Zhao J, Kucuksari S, Mazhari E, Son Y-J. Appl Energy 2013;112:35–51.
[77] Lujano-Rojas JM, Monteiro C, Dufo-López R, Bernal-Agustín JL. Energy Policy 2012;45:671–9.
[78] Druitt J, Früh W-G. J Power Sources 2012;216:104–16.
[79] Valentine K, Temple WG, Zhang KM. J Power Sources 2011;196:10717–26.
[80] Tehrani N, Shrestha G, Wang P. In: Power and energy society general meeting (PES). IEEE; 2013. p. 1–5.
[81] Darabi Z, Ferdowsi M. In: Power and energy society general meeting. IEEE; 2011. p. 1–8.
[82] U.D. of transportation, F.H. administration. National household travel survey; 2013. Available at: ⟨http://nhts.ornl.gov⟩.
[83] Kelly JC, MacDonald JS, Keoleian GA. Appl Energy 2012;94:395–405.
[84] Bae S, Kwasinski A. IEEE Trans Smart Grid 2012;3:394–403.
[85] Hahnel UJ, Golz S, Spada H. Transp Res Part A: Policy Pract 2013;48:123–31.
[86] Bashash S, Moura SJ, Forman JC, Fathy HK. J Power Sources 2011;196:541–9.
[87] Kristoffersen TK, Capion K, Meibom P. Appl Energy 2011;88:1940–8.
[88] Acha S, van Dam K, Shah N. In: 2012 IEEE power and energy society general meeting; 2012. p. 1–8.
[89] He Y, Venkatesh B, Guan L. IEEE Trans Smart Grid 2012;3:1095–105.
[90] Shah N, Cho B, Geth F, Clement K, Tant P, Driesen J. In: 2011 IEEE vehicle power and propulsion conference (VPPC); 2011. p. 1–6.
[91] Johnson J, Chowdhury M, He Y, Taiber J. Transp Res Part C: Emerg Technol 2013;26:352–66.
[92] Hattori Y, Shimoda T, Ito M. In: 75th IEEE vehicular technology conference. VTC Spring; 2012. p. 1–6.
[93] Malandrino F, Casetti C, Chiasserini C. In: IEEE 23rd international symposium on personal indoor and mobile radio communications (PIMRC); 2012. p. 2541–6.
[94] Hori Y. In: 2010 international power electronics conference (IPEC); 2010. p. 2930–4.
[95] Rahmani Rasoul, et al. Hybrid technique of ant colony and particle swarm optimization for short term wind energy forecasting. J Wind Eng Ind Aerodyn 2013;123:163–70.
[96] Seyedmahmoudian Mohammadmehdi, et al. Maximum power point tracking of partial shaded photovoltaic array using an evolutionary algorithm: a particle swarm optimization technique. J Renew Sustain Energy 2014;6(2):023102.
[97] Seyedmahmoudian M, Mekhilef S, Rahmani R, Yusof R, Renani ET. Analytical modeling of partially shaded photovoltaic systems. Energies 2013;6(1):128–44.
[98] Rahmani R., et al. A complete model of stand-alone photovoltaic array in MATLAB-Simulink environment. In: Proceedings of the 2011 IEEE student conference on Research and Development (SCOReD); 2011.